Smart Meter Reference Load Profiles and Peak Demand Models

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Abstract. Smart grids are components of future clean energy systems. They create new challenges and opportunities for the efficient and reliable management of the electricity system. The aggregate behaviour of groups of electricity users, such as the magnitude and timing of peak demand are important factors in determining the required capacity of the Low Voltage (LV) distribution network in the context of a transition to low carbon heat and transport. In this paper we use smart meter data from consumer behaviour trials in Ireland to create Reference Load Profiles (RLPs), and to model peak residential electricity demand. We find differences in the peak demand and profile by day type, and that Burr, and Weibull models are useful to estimate peak demand.

Keywords: Reference Load Profile · Smart Grid · Peak Demand Model

1 Introduction: Clean Energy Targets

The EU aims to achieve climate neutrality by 2050 and has set targets for its member states [7]. Ireland, an EU member, has set out its clean energy and climate plans in [14, 9]. The transport and residential sectors account for approximately two thirds of overall energy consumption representing, respectively, 17.1% and 9.0% of the total amount of greenhouse gas emissions in Ireland in 2022 as per the Climate Action Plan 2023 (CAP23) progress reports [12]. Much of this energy is currently sourced through fossil fuels. The electrification of heat and transport will change the energy balance model and will significantly increase the requirements on the electrical distribution network infrastructure.

Electricity distribution systems are typically planned and dimensioned to facilitate the expected maximum demand of groups of users. The After Diversity Maximum Demand (ADMD) measure is used by Distribution System Operators (DSO) in the design of distribution networks where coincident demand is aggregated over a sample of customers. Traditional statistical models that underpin the design rules and approaches are based on historical consumption data from small samples of customers. Such models were appropriate when consumption patterns were relatively homogeneous. However, the adoption of low carbon technologies such as heat pumps, electric vehicles, photovoltaic generation and energy storage will change these patterns. DSOs and other agents must reassess residential load models, especially peak load, to facilitate network dimensioning and investment planning. The availability of smart meter data will allow more reliable models of residential energy consumption to be created.

In this paper, we review residential Reference Load Profile (RLP) creation methods and peak demand estimation techniques. We then propose and evaluate statistical models using smart meter data from consumer behaviour trials conducted in Ireland. We focus on answering the following research question:

1. Are there differences in RLPs by day of the week?
2. Which statistical models are a good fit to residential peak load distributions?

We find that there are significant differences in RLPs by day and that Burr and Weibull models offer useful approaches to model peak residential demand.

2 Residential Electricity Load Modelling

Challenges from the uptake of heat pumps are outlined in [15]. National scale problems include peak demand and ramp rate increase. At the local scale the Low Voltage (LV) distribution network may experience excessive voltage drop and insufficient thermal capacity of the LV feeder and transformer. The impact of electric vehicles on the grid are assessed in [5]. They suggest that a coordinated charging approach is needed to allow the mass adoption of electric vehicles so that power losses can be minimised and the load factor can be maximised.

Before anticipating future load issues, we first need to understand current residential RLPs and peak demand patterns. Paatero et al. [20] describe statistical modelling and simulation of two Finnish hourly appliances and lighting data sets from 1082 households/buildings to create residential RLPs. The focus in [22] is on load patterns for consumer groups using frequency domain analysis. They note the smoothed load patterns when taking the average over the group and rely on the customer class group defined by the utility company suitable for the customers' needs and lifestyle.

In contrast, Irish smart meter data [8] is used in [11] to clustering consumers with similar usage patterns. An analysis of the clusters finds that how strongly householders feel can convince other occupants of the building to reduce their energy usage is a significant factor in cluster membership. A machine learning approach to creating RLPs is described in [19]. They compare Symbolic Aggregate ApproXimation (SAX) with other data reduction techniques for electricity load profile clustering using a sample of high resolution load data for 234 consumers at 15-minute intervals. Multiple linear regression is used by [18] to explore bottom-up approaches to load modelling: a dwelling and occupant characteristics model to describe consumption patterns of various households; and an electrical appliances model describing how electricity is consumed. The results show that occupant characteristics (head of household age, and household composition) impact peak electricity consumption times.

Next we consider peak demand models. Early standards to estimate residential peak demand are described in [1]. Mean demand is estimated from field measurements. The model allows for variability due to customer behaviour due to temperature and other causes. A simple regression model is used: $\overline{D} = P + Q/\sqrt{N}$, where $\overline{D}$ is the average demand, P and Q are regression coefficients, and N is the portfolio size (number of customers). They fit models per customer type and per half hour intervals and focus on winter peak demand, historically highest in temperate climates like Ireland and the UK. Meeting demand with a 90% probability was deemed an appropriate risk level.

Next we consider the digitalisation of the electricity system. Both statistical and machine learning approaches offer insights from the digitised grid but face limitations, including challenges in reconciling the discrepancies between the empirical evidence from metered data and outputs from simulations based on statistical models as outlined in [21]. Smart Meters (SMs) are crucial for EU greenhouse gas reduction and renewable energy goals [6]. Ireland's National Smart Metering Programme was announced in 2017 [4]. The rollout is to be completion by 2024 using the high level design enabling daily data transfer between consumers and suppliers [3]. SM infrastructure will significantly increase the amounts of data collected by participants in electricity markets [10]. This will aid accurate residential energy consumption models and policy design. SMs also enable customer engagement via tariffs and Demand Side Response (DSR), vital for economic transition to low carbon economy, integrating Renewable Energy Source (RES) and technologies like heat pumps and Electric Vehicles (EVs). Smart meter data availability may address concerns raised in [21] and [20]. Bottom-up models in [20] are used to test several DSR strategies, assuming household loads can be managed separately to enable DSR measures on an individual appliance level simultaneously in several households. They do not discuss household appliances management technology, their main concern is to understand how to adjust load profiles to reduce peak demand by shifting some appliance demand to off-peak times. New rules and protocols concerning data collection and communication between the different participants in the market are being developed. However, concerns about privacy arise with smart meters [17]. For example, third parties may intercept signals for illegal purposes, allow intrusive surveillance of the individuals'usage for purposes other than billing and may lead to unfair tariff design practices. Such concerns must be addressed in strategic energy technology implementation plans.

3 Methodology

We focus on developing useful models to answer our two research questions using smart meter Customer Behaviour Trial (CBT) data available from [8]. The Irish regulator, Commission for Energy Regulation (CER), conducted a large scale smart meter CBT in 2009-2010 to assess the performance of smart meters and their impact on consumer behaviour. The CBTs aimed to assess customer response to price incentives. The anonymised trial data are available for research purposes.We note that, as the Smart Meter Data (SMD) are anonymised, we cannot say where on the network these customers reside.

The CER used a stratified random sampling framework to ensure a representative sample in terms of household size, geographic location, and socio-economic indicators. Over 5,000 participants were recruited, each representing a household, i.e. a number of persons sharing a single residential unit. Pre- and post-trial surveys focused on electricity usage attitudes, trial expectations, dwelling and electrical appliances. The CBT recorded electricity usage at half-hourly intervals, producing 269 MB of time-series data per household. Participants' half-hourly KW usage data from July to December 2009 served as benchmark. After this, the CBT participants were divided into test and control groups to test tried different tariffs and Demand Side Management (DSM) stimuli.

The trial ran from January to December 2010, coinciding with severe weather events. We focus on the benchmark period. We removed meters of participants who dropped out or where technical issues that caused significant data loss. We created several views of the data in order to answer our research questions. We aggregated the kW half hour data by day of the week to calculate average daily half hourly load profiles. Peak demand values (kWhh) and their occurrence times were extracted per customer daily to create distributions of peak demand patterns. Peak demand time series were smoothed by averaging for each meter per day type during the benchmark period. The tagged data by day (i.e., Monday, Tuesday, . . .) allows us to compare weekend to weekday profiles. A sample of average peak half hour kW demand by day is shown in Table 1.

Table 1: Sample Peak Daily Average Demand (kWhh)

Meter Id	Number Occupants	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1002	1	0.7100	0.6754	0.8407	0.7582	0.7390	0.7685	0.6724
1003	3	2.3253	2.3231	2.4708	2.3898	2.3441	2.4913	2.5336
1004	4	4.7401	4.6716	4.6140	4.0250	4.3486	4.4139	4.7045

Note that we use half-hourly kW data resolution to align with Ireland's single electricity market practices. Occupancy per household is available in the CBT survey data, which is crucial for load models as noted in [18]. However, this data will not be available in Ireland's smart meter rollout [3].

We also created another view of time-series load data, similar to the approach taken in [2]. We reduce the data in size by calculating explanatory variable/features of the data such as the moments (mean, variance, skewness) and other descriptive statistics for each household such as the time and values of the peak usage during the morning periods. We then built and tested several statistical models under the following headings:

1. RLPs - Exploratory Data Analysis;
2. Peak Demand - Probability Density;
3. Peak Demand - General Linear Models.

Firstly, we evaluate the distance between the weekday and weekend average RLPs, and identify the time when peak demand occurs. Next we conduct univariate analysis of the peak demand and evaluate the fit of several probability density functions from the exponential family of distributions. Metrics such as the log likelihood, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Kolmogorov-Smirnov D (KS), Anderson-Darling (AD) and Cramer-von Mises W-Sq (CvM), are used to assess the Goodness of Fit (GOF) of the statistical Probability Density Function (PDF) to the Empirical Density Function (EDF). These metrics quantify the distance between the Probability Density Function (PDF) and Empirical Density Function (EDF) in different ways and seek the most parsimonious model by penalising models with more parameters. The lower the distance scores the better the model fit.

Finally, we evaluate General Linear Models (GLM) for peak demand and occupancy time. These extend the simple linear regression model in [1]. Data is divided 60:20:20 for train, validate, and test subsets. We employ elastic net approach to regularisation to mitigate over-fitting, yielding balanced regression models between number of coefficients and their size. Various metrics determine the best-fitting GLM regression model and parameter values for empirical data.

4 Results and Analysis

Recall our primary research questions relate to RLP and peak demand models. Question 1 asks if there differences in RLPs by day of the week. Analysis of the daily load profiles (averaged per customer per day), show similarities among weekdays, and stronger differences between weekdays and weekend days. This is consistent with the findings in [20, 18]. Figure 1 shows the average load profiles per customer by day type over the benchmark period.

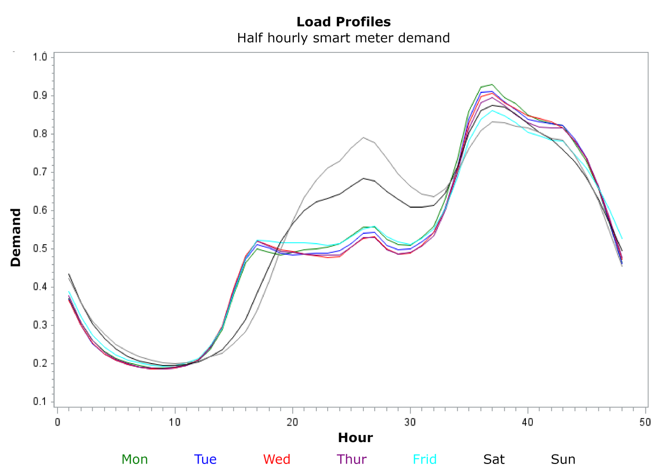


Fig. 1: Reference Load Profile (RLP) by day

Figure 2 shows a dendrogram for the clustered daily RLPs. Midweek days show the strongest similarities. We can see more clearly that weekdays form one cluster and that weekend days form a second cluster. Within those clusters we can see that there are some differences between the weekdays. Public holidays in Ireland generally occur on Mondays, the dendrogram shows that for example Mondays are somewhat dissimilar to other weekdays. The clustering shows that Fridays are also a bit different to the other weekdays.

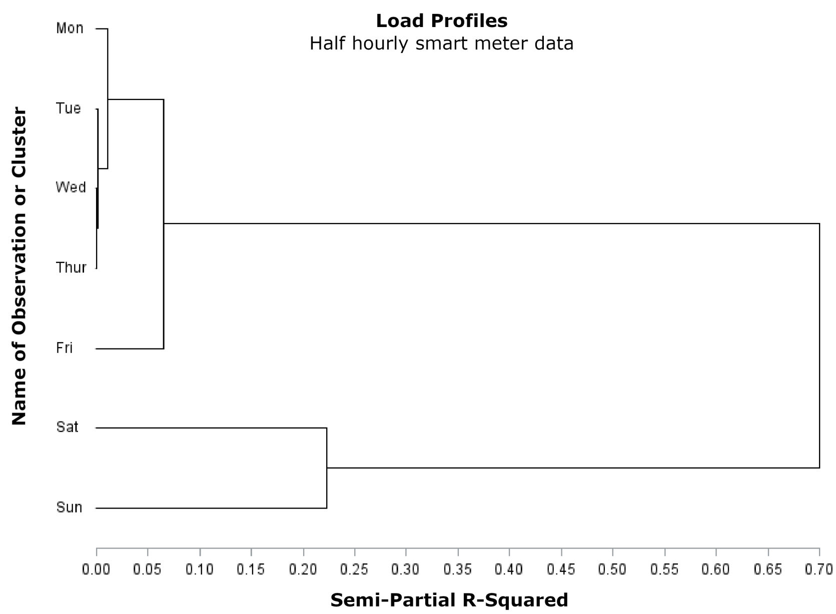
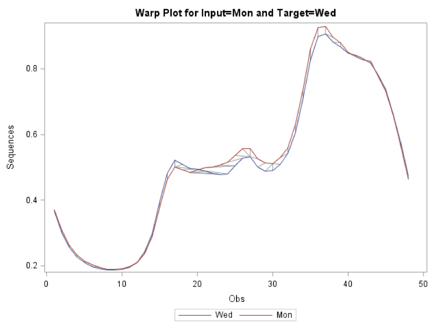
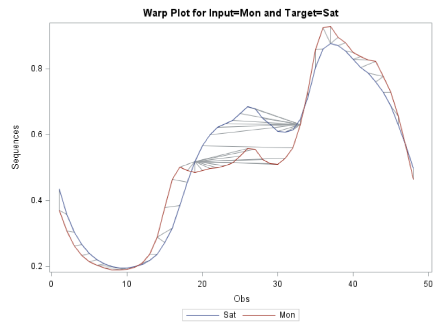


Fig. 2: Reference Load Profile (RLP) Cluster Dendrogram

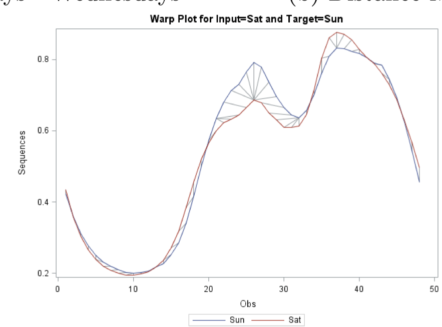
We also see some differences between Saturdays and Sundays. Figure 3 shows the distances between sample weekday and weekend day types. We can again see that the biggest difference is between weekday and weekend patterns of behaviour. In particular we note the difference in Figure 3b in terms of the height of the peaks, since the LV network must be dimensioned to cater for the higher of the two. We next address our second research question and report on the statistical models that offer a good fit to residential peak load distributions. Recall we processed the data to create a view of the peak demand for each customer each day. Figure 4 shows the distributions of peak demand per consumer in kW half hour for weekdays and weekends over the benchmark period. We see relatively high kW values reported for the 90, 95 and 99 percentiles and note that on all days the pattern of peak demand is right skewed. This tells us a small number of consumers generate high demand.



(a) Distance Mondays - Wednesdays



(b) Distance Mondays - Saturdays



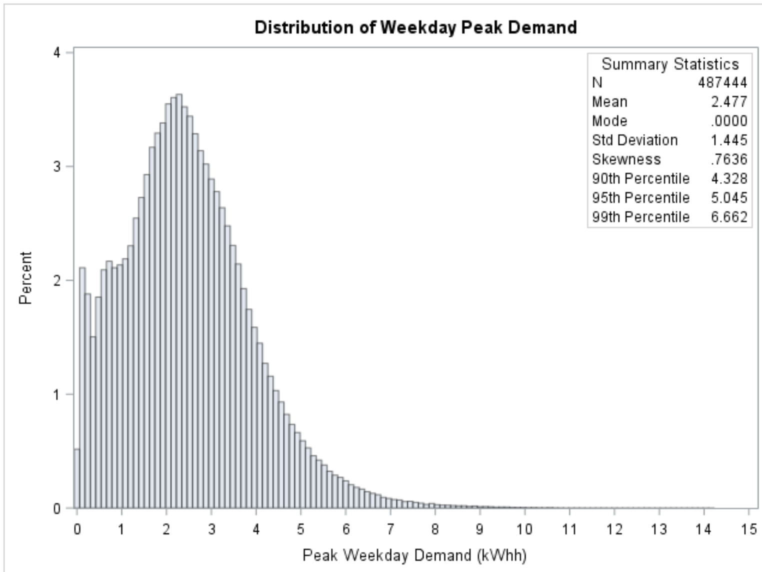
(c) Distance Saturdays - Sundays

Fig. 3: Comparison of Reference Load Profile (RLP) by day type

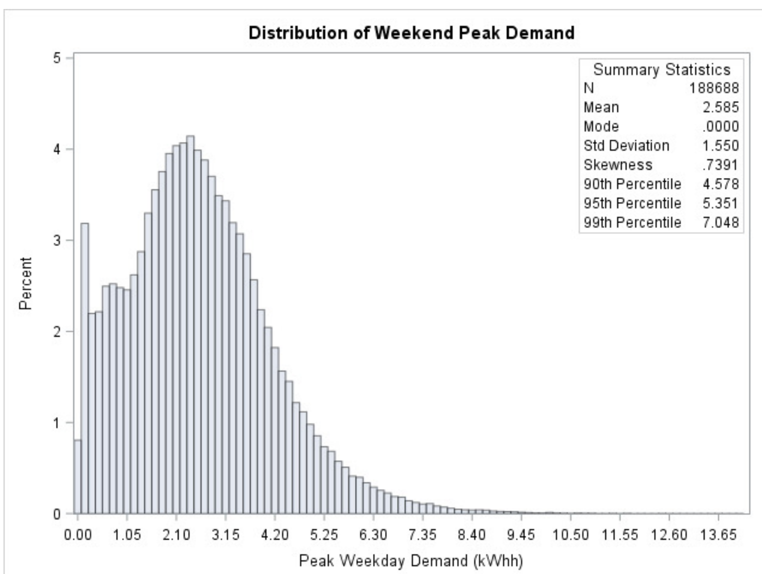
Comparing the empirical distribution of average peak demand on Mondays (a weekday) with Saturdays (a weekend day), we see evidence in Figure 5 that the distributions are different, and that the average peak residential demand on Mondays is higher than on Saturdays. Statistical tests confirm the hypothesis, $p = 0.0035$ from a Kolmogorov-Smirnov Two-Sample Test.

The right tailed empirical patterns we observed suggest a probability density from the exponential family of distributions could be used to model the peak demand. We test the fit of a number of models from the exponential family to the average peak demand. Preliminary analysis shows that Burr and Weibull models are a good fit for the distributions of average Monday peak demand. Table 2 shows sample model fit metrics for average peak Monday demand. The log likelihood measure suggests the Burr mode as the best fit, all the other metrics suggest the Weibull model. The Weibull is a simpler model (i.e., has less parameters), and may be more familiar to the electricity community as it is used to fit wind power models, e.g., [16].

Figure 6 shows the Burr and Weibull PDFss fitted to the empirical data, and both offer reasonable solutions. Similarly, looking at Saturdays (typical weekend days), Burr and Weibull models offer a good model fit of average peak demand, see Figure 7.



(a) Weekday Peak Demand Distribution



(b) Weekend Peak Demand Distribution

Fig. 4: Comparison of weekday and weekend Peak Demand

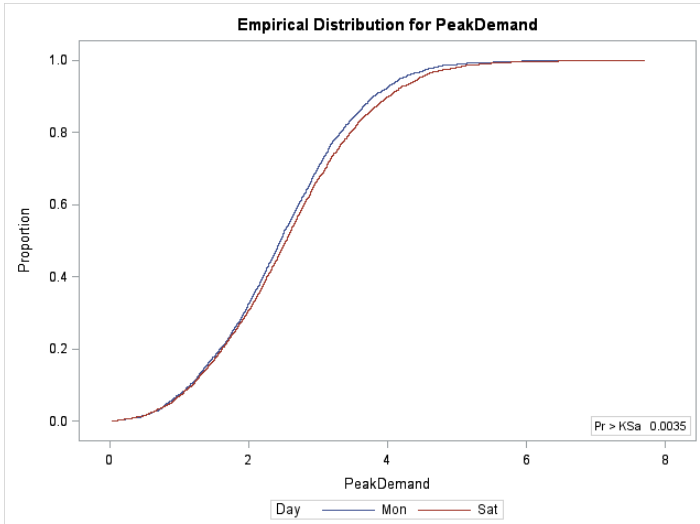


Fig. 5: Distance between the average peak demand empirical distributions on Mondays versus Saturdays

Table 2: Sample PDF model fit results (Mondays)

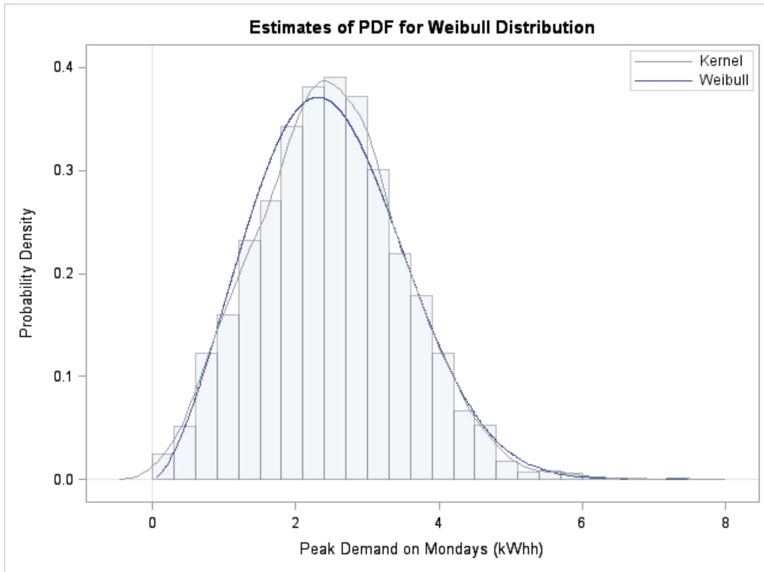
Distribution	-2 Log Likelihood	AIC	BIC	KS	AD	CvM
Burr	11293	11299	11318	1.50	3.00	0.51
Exp	15015	15017	15024	17.43	601.71	118.99
Gamma	11629	11633	11646	4.07	30.23	5.28
Igauss	13064	13068	13080	8.93	146.75	28.63
Logn	12378	12382	12395	6.17	79.33	13.58
Pareto	15016	15020	15032	17.44	601.76	119.00
Gpd	15015	15019	15032	17.43	601.71	118.99
Weibull	11294	11298	11311	1.49	2.94	0.51

In summary we suggest two-parameter Weibull models for average peak demand. The two-parameter Weibull model PDF is given by:

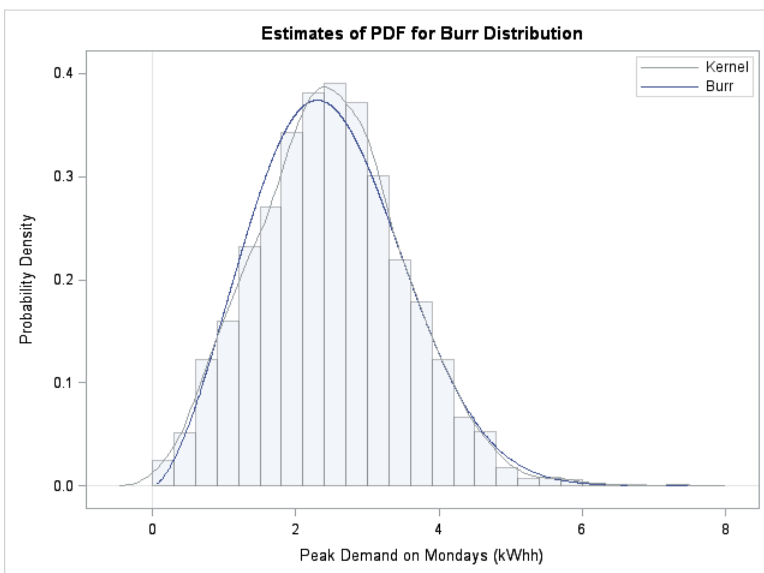
$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{1}$$

where β is a shape parameter and η is a scale parameter.

In further analyses, we are interested in when peak demand of the individual consumers occurs, as the LV network design is concerned with coincident peak load. In all the RLPs, we see that aggregate peak demand occurs in the evening

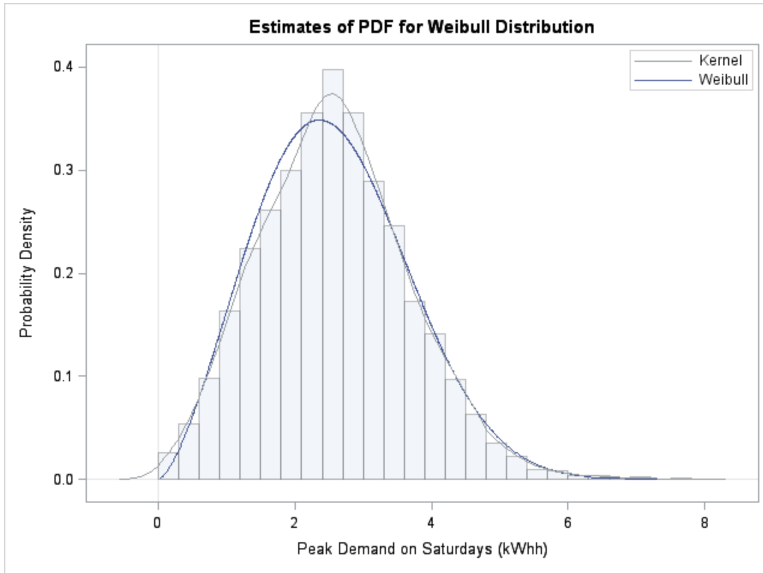


(a) Average Monday Peak Demand: Weibull

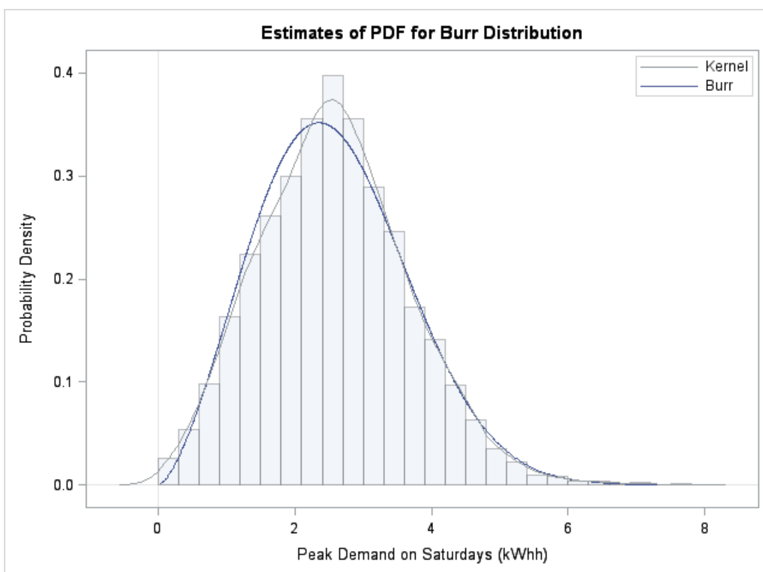


(b) Average Monday Peak Demand: Burr

Fig. 6: Comparison of Weibull and Burr models for average Monday Peak Demand



(a) Average Saturday Peak Demand: Weibull



(b) Average Saturday Peak Demand: Burr

Fig. 7: Comparison of Weibull and Burr models for average Saturday Peak Demand

hours. Taking a different view of the data, we examine the peak demand per consumer and explore when that occurs. Figure 8 shows the half hour time slot when peak demand occurs for the sample of consumers in the CER CBT over the benchmark period. We see the mode for peak usage is at 18.00 on the 24 hour clock (the 36^{th} half hour, with the average at approximately 16.00. We see a degree of variability in when consumers generate their peak demand. It is interesting to observe that some customers have complementary timing of peak usage to the norm, with a small percentage (approx. 5%) generating their peak demand in the hours just after midnight.

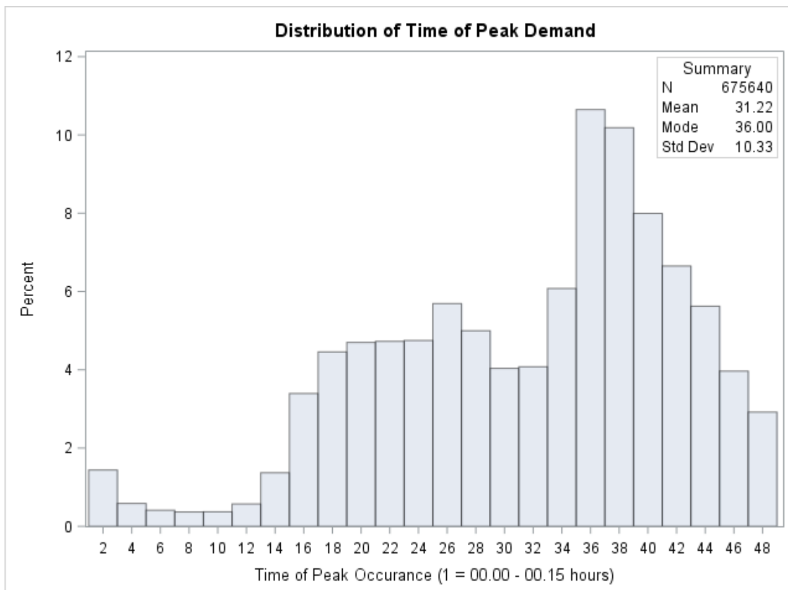


Fig. 8: Time of Peak demand occurrence

We note that it may be useful to create separate Weibull models per day type or per time step, e.g., we estimate parameters for average Monday peak demand as $\beta_M = 2.582$ and $\eta_M = 2.792$, in comparison to $\beta_S = 2.500$ and $\eta_S = 2.897$ where the M and S subscripts denote the day name.

In our final set of analyses, we report results for the GLM models which are an extension to the simple linear regression model in [1]. Several models were tested using the time series reduced data described and were successful at predicting the average peak demand, but the GLM models did not prove useful to also predict the time of peak demand occurrence.

For brevity we report one of the useful models for average peak demand which returns an R^2 value of 0.92 indicating the model can explain 92% of the variation in average peak demand. The residual errors are approximately normally distributed suggesting the linear model is a good fit. The estimated coefficients provide the following multiple linear regression model:

$$\begin{aligned} APD = 2.386 * SD + 0.091 * max - 0.949 * MORNMAX \\ + 1.099 * mean + 0.822 * MORNPEAK + 0.283 * MORNRANGE \end{aligned} \quad (2)$$

Where APD is the Average Peak Demand, SD is the Standard Deviation, max is the maximum of the consumer's daily peak demands in the sample, MORNMAX is the Maximum Energy Usage During Morning Periods (kWhh summed over the morning time slots), mean is the average usage, MORNPEAK is the value of the Peak Usage During the Morning, and finally, MORNRANGE is the Range of Usage in the Morning Hours (06.00 - 10.00). These explanatory variables were all reported as significant ($p < 0.0001$), the intercept coefficient was not statistically significant.

Again, the regression models could be further developed by parameterising per time slot or day type. The addition of other explanatory variables and interaction terms created models with higher R^2 values. However this came at the risk of over-fitting and an increase in the complexity of the model.

5 Discussion and Conclusion

This paper explores the methods used to create RLPs and develop models for peak residential electricity demand, also making a novel contribution in providing insights into the PDFs and regression models suitable to model peak demand. These models will be useful to those concerned with evaluating the capacity of Photovoltaic (PV) distribution networks and provide a rigorous starting point from which to evaluate scenarios for new end-use applications in the smart grid. This models will present opportunities to de-risk investment decisions with use of these appropriate models.

We acknowledge the limitations of our work, as with all statistical model fitting, there is a risk of over-fitting. We have used machine learning data reduction approaches rather than traditional time-series approaches. In future research we may compare the two approaches. In addition, the CBT took place in 2009. Improvements in electrical appliances and building energy ratings can reduce consumption, although the rate of change is relatively slow since the life cycle of homes and appliances is relatively long, and the average annual usage has not changed significantly to date. Applying our analysis to more recent data would be a useful next step. However, General Data Protection Regulation (GDPR) and commercial sensitivity concerns have impeded the availability of open source smart meter data for research. Data sharing agreements and new business models which allow consumers extract value from their data are needed. As noted in [13], interest in local supply markets mainly comes from new actors such as local energy community groups, social enterprises and municipalities. Such groups may be interested in developing innovative business models to share and extract value from smart meter data. Meanwhile, the Irish CBT remains one of the most cited smart meter studies. The large sample size and the quality of the study design which ensured the quality and reliability of the data.

We have presented several useful reproducible models. As the grid becomes further digitised, data from consumers and their end-use applications will become more widely available subject to the limitations we have noted. The study methods could be implemented by electricity network operator using their own data and could also be used as a prototype for electricity market participants to derive value from new smart meter data sources. We argue that our models have their uses in facing the challenges of resolving conflict between fast paced technological innovation and slower/longer term investment decisions when the need for transformation to achieve climate change targets is so urgent.

We conclude that the differences in weekend and weekday usage patterns suggest RLPs per day type should be considered. In response to our research question on which statistical models offer a good fit to residential peak load distributions we conclude that Weibull models describe the average peak demand PDFs well, and that multiple linear regression models are useful to provide estimates of average peak demand for a portfolio of consumers.

We see that there is potential for further development of the models recommended by our study. In particular we intend to tailor the Weibull peak demand models per time slot t by parameterising the model: $\beta \to \beta_t$ and $\eta \to \eta_t$.

Finally, in this study we have not addressed the challenges of ensuring data privacy and fairness to all consumers. We acknowledge in the context of the Big Data revolution that this is a major concern that must be addressed in smart energy transition implementation plans.

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